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AI-Driven Career Guidance System: A Predictive Model for Student Subject Recommendations Based on Academic Performance and Aspirations

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Abstract

This study presents an AI-based predictive model designed to forecast potential career paths for students based on academic performance, extracurricular activities, and personal aspirations. Traditional career guidance methods, such as standardized assessments and counselling, often lack the personalization necessary to cater to individual student needs, particularly in a rapidly changing educational landscape. To overcome these limitations, this research employs advanced neural network architectures, specifically Encoder-Decoder Long Short-Term Memory (LSTM) models, to analyse data on academic performance, demographic factors, and student aspirations. The dataset used in this study includes academic scores in math, reading, and writing, along with demographic information such as gender, parental education level, and test preparation status. The data was pre-processed to handle missing values, standardize scores, and encode categorical variables, ensuring the model's inputs were clean and consistent. Feature engineering was performed to extract meaningful insights, such as average performance across subjects, deviations from class averages, and alignment of performance with potential career paths. The core of the model is an Encoder-Decoder LSTM architecture designed to capture temporal dependencies and sequence patterns within the student data. The encoder processes sequences of academic scores and demographic features, generating a context vector that encapsulates the student's academic profile. The decoder then uses this vector to produce recommendations for potential career paths and subject choices, offering personalized guidance tailored to each student's strengths and aspirations. Key findings indicate that the AI-driven recommendations closely align with traditional guidance while offering enhanced personalization. The model achieved a high accuracy rate, demonstrating its ability to understand and predict optimal subject choices for students. Comparisons with traditional methods showed that the AI model provided more individualized guidance, reflecting each student's unique academic journey and personal goals. This research highlights the transformative potential of AI in educational decision-making, providing actionable insights that can help students make more informed choices about their academic and career paths. Ethical considerations, such as data privacy and bias mitigation, were addressed throughout the study to ensure responsible AI deployment. Measures were taken to anonymize student data and regularly audit the model for biases related to gender and socio-economic status. These steps are critical in maintaining the integrity and fairness of AI-driven recommendations in educational contexts. This research underscores the importance of integrating ethical guidelines into AI systems, ensuring they serve as trusted tools that enhance, rather than undermine, educational equity and personalization.

Keywords: *AI, career guidance, predictive model, student performance, subject recommendation, ethical AI, neural networks, LSTM, Encoder-Decoder, and Students Performance in Exams dataset.*

I. Introduction

In recent years, the quality of education has increasingly been evaluated based on student performance, which reflects the effectiveness of the learning environment. Numerous studies have emphasized the significance of early learning stages in shaping students' academic journeys, where the initial grasp of subject content and syllabus structure can build a strong foundation for subsequent courses and learning experiences. Effective early intervention in education, such as tailored guidance and personalized learning, plays a critical role in keeping students engaged and motivated, reducing the likelihood of academic struggles later on. Traditional guidance methods, such as counselling and standardized assessments, often fail to provide the personalized support students need to excel, highlighting a need for more innovative approaches to academic guidance.

With the advent of digital education platforms and the increasing accumulation of student data, educational institutions now have access to vast amounts of academic performance information. However, this data often remains underutilized, trapped within institutional information systems without being leveraged to inform teaching or improve student outcomes. In parallel, the field of artificial intelligence (AI) has seen rapid advancements, with AI applications transforming industries like healthcare, manufacturing, and finance. These advancements are driven by the integration of big data analysis and AI algorithms, which uncover patterns and make data-driven decisions that were previously impossible.

In the educational sector, AI has shown significant promise in enhancing student performance prediction and career guidance. Educational data mining, a rapidly growing field, aims to extract valuable insights from student data to improve learning outcomes and provide early warnings of academic challenges. Despite progress in AI-based student performance prediction, existing methods are often constrained by a focus on e-learning platforms, which do not fully address the needs of traditional classroom settings. Furthermore, many current models provide predictions only during or near the end of courses, which limits their ability to address early-stage learning difficulties [12]. There is also a lack of models that consider the complex relationships between different subjects and student interests, which are essential for personalized career guidance.

To address these challenges, this research focuses on developing an AI-driven subject recommendation system using the Students Performance in Exams dataset. This dataset includes students' scores in core subjects such as math, reading, and writing, along with demographic information like gender, race/ethnicity, and parental education levels. By integrating this data with advanced machine learning techniques, the study aims to provide personalized subject recommendations that align with students' academic strengths and interests.

The primary objective of this study is to enhance traditional career guidance methods by utilizing a Recurrent Neural Network (RNN) with an Encoder-Decoder architecture to analyze diverse student data. This approach allows for the extraction of deeper insights from student performance data, enabling the generation of tailored subject recommendations that reflect both academic capabilities and personal preferences. The key contributions of this research are as follows:

- **Development of a Novel AI-Based Subject Recommendation System**: For the first time, the use of an RNN-based Encoder-Decoder model is proposed to predict potential career paths for students based on their performance data, addressing the limitations of traditional guidance methods.
- **Integration of Academic and Aspirational Data**: This study combines academic performance metrics with student aspirations and interests, captured through structured questionnaires, to provide a holistic view of each student's potential career trajectory.
- **Evaluation of AI-Driven Recommendations against Traditional Methods**: The research includes a comparative analysis of AI-based recommendations with conventional guidance techniques, demonstrating the effectiveness and added value of the proposed system in enhancing decision-making and student satisfaction.

II. Related Work

Jie Yang et al. (2021) introduced a discriminable multi-label attribute selection (DMAS) algorithm to predict pre-course student performance, aiming to accurately identify relevant attributes that contribute to performance prediction, which is valuable for early intervention strategies in educational settings. Ali Daud et al. (2017) explored the use of learning analytics in predicting student performance, focusing on data analysis techniques that help identify at-risk students early and facilitate timely educational interventions. Zawqari et al. (2022) studied the prediction of academic performance in online courses using flexible feature selection methods, emphasizing the importance of identifying key factors that contribute to student success. Maryam Zaffar et al. (2018) analyzed various feature selection algorithms for predicting academic performance, comparing their effectiveness in selecting the most relevant features that enhance prediction accuracy. Abeje Orsango Enaro et al. (2018) examined data mining techniques for feature selection in student performance prediction, highlighting the evaluation of different algorithms to determine their efficiency and suitability in educational contexts. Nalindren Naicker et al. (2020) employed linear support vector machines (SVM) to predict student performance, demonstrating the algorithm's ability to classify educational data and its effectiveness in academic performance prediction.

Safira et al. (2022) combined genetically optimized feature selection with multiclass classification techniques, improving the accuracy of student performance predictions through the integration of genetic algorithms. V. Vijayalakshmi et al. (2019) proposed a deep neural network architecture for predicting student performance, showcasing the potential of deep learning techniques in educational data analysis. Yahia Baashar et al. (2022) utilized artificial neural networks (ANNs) for academic performance prediction, exploring the model's design and training processes to enhance predictive accuracy. Sujan Poudyal et al. (2022) evaluated a novel 2D CNN-based architecture combined with other techniques to predict student performance, highlighting the benefits of deep learning and hybrid models in this context. Kaiming et al. (2015) provided insights into residual learning through the ResNet architecture, demonstrating its potential for achieving higher accuracy in complex predictive tasks. Ian J. et al. (2019) discussed generative adversarial networks (GANs), focusing on their framework and applications in generating realistic data for improved predictive modeling. Ashish Vaswani et al. (2017) detailed the Transformer model's architecture, emphasizing its ability to capture long-range dependencies and its advantages in natural language processing tasks, which are increasingly relevant in educational data analysis.

Volodymyr Mnih et al. (2013) combined deep Q-learning with convolutional neural networks (CNNs) to enhance performance prediction models, showcasing the integration of reinforcement learning with deep learning for complex decision-making scenarios. Alec Radford & Luke Metz et al. (2016) introduced deep convolutional generative adversarial networks (DCGANs), demonstrating their ability to learn hierarchical representations and generate realistic data without labeled training data. M. Riki Apriyadi et al. (2022) proposed a hybrid approach integrating particle swarm optimization (PSO) and genetic algorithms for feature selection, aiming to improve support vector regression (SVR) models by optimizing feature relevance. Deepti Aggarwale et al. (2019) analyzed various machine learning algorithms and feature selection methods, discussing their strengths and limitations in predictive analysis of academic performance. Phauk Sokkhey et al. (2020) evaluated feature selection techniques to identify the most influential factors in academic performance prediction, providing insights into the impact of specific variables on predictive accuracy. Prasanalakshmi Balaji et al. (2021) reviewed machine learning techniques for academic performance prediction, offering a comprehensive overview of the current methodologies and potential areas for further research.

AYA NABIL et al. (2021) proposed a deep neural network designed to predict academic performance by considering sequential course data, emphasizing the model's potential for early identification of at-risk students. Reshmy Krishnan et al. (2019) explored filter ranker algorithms to assess gender-based differences in academic performance, contributing to the understanding of demographic influences on educational outcomes. Wilson et al. (2021) enhanced performance prediction in intelligent tutoring systems (ITS) using attribute selection and ensemble models, demonstrating the benefits of integrating multimodal data sources for accurate predictions. Balqis Al Breiki et al. (2019) employed educational data mining techniques, such as classification and clustering, to predict student performance, highlighting the role of data mining in identifying at-risk students and optimizing educational interventions. Sebastianus Radhya et al. (2022) synthesized the current state of machine learning applications in education, identifying trends and challenges in performance prediction models. Maria Koutina et al. (2011) utilized machine learning techniques to predict postgraduate student performance, emphasizing the application of decision trees, logistic regression, and neural networks in educational contexts.

T. Velmurugan et al. (2016) evaluated feature selection algorithms in educational data mining, comparing their performance to determine the most effective methods for improving predictive accuracy. Roberto Bertolini et al. (2021) combined feature selection with cross-validation techniques to enhance the generalizability of performance prediction models, addressing overfitting and improving model reliability. Celia González Nespereira et al. (2015) employed machine learning to classify student performance in blended learning settings, aiming to enable personalized educational interventions. Kongara Deepika et al. (2018) integrated the Relief-F feature selection algorithm with Budget Tree Random Forest to improve the interpretability and accuracy of student performance predictions. Md. Ahsan Arif et al. (2021) combined classification models, such as decision trees, with feature selection techniques to enhance predictive efficiency, facilitating personalized support for students. Jyoti Namdeo et al. (2014) utilized rough set theory to identify relevant features in academic performance prediction, focusing on attribute reduction to improve model accuracy. Phauk Sokkhey et al. (2020) applied educational data mining techniques to develop web-based systems for predicting underperforming students, emphasizing the integration of predictive models in educational management. Raza Hasan et al. (2020) analyzed video learning data to identify patterns in student engagement and performance, demonstrating the application of data mining in video-based educational analytics. Gomathy Suganya Ramaswami et al. (2020) explored various feature selection approaches in educational data mining, assessing their impact on predictive model performance. Teo Susnjak et al. (2021) utilized learning management systems (LMS) data for academic success prediction, highlighting the importance of feature selection methodologies for early prediction. Dr. K. Karthikeyan et al. (2017) reviewed conventional and improved methods for performance prediction, focusing on the development of algorithms tailored to educational data.

Table 1. Related studies for student performance prediction task.

Authors	Year	Features
Macfadyen and Dawson	2010	Predictive modeling of students' final grades using factors such as student discussions, emails sent, and test completion.
Zafra et al.	2011	Use of quizzes, assignments, forums, and other course information to predict student pass/fail outcomes.
Sweeny et al.	2015	Predicting students' grades for the next semester based on previously completed course grades.
Ren et al.	2016	Applying data from MOOC server logs to predict student learning outcomes.
Conijn et al.	2018	Predicting student performance and identifying potential areas for improvement in MOOCs.
Oswaldo et al.	2019	Comparing various educational data mining algorithms to explore research trends and graduation patterns.
Ma et al.	2020	Multi-instance multi-label learning for predicting pre-course student performance.
Ma et al.	2020	Integrating multi-instance multi-label learning with multi-task learning for pre-course performance prediction.
Jie Yang et al.	2021	Discriminable multi-label attribute selection to enhance prediction of pre-course student performance.
Ali Daud et al.	2017	Learning analytics used to predict student performance by analyzing academic and engagement data.

Zawqari et al.	2022	Flexible feature selection for predicting performance in online courses, focusing on relevant student data points.
Maryam Zaffar et al.	2018	Evaluation of different feature selection algorithms for their effectiveness in performance prediction.
Abeje Orsango Enaro et al.	2018	Data mining approaches to feature selection in predicting academic performance using various algorithms.
Nalindren Naicker et al. [	2020	Use of linear SVM models to classify educational data for predicting student performance.
Safira et al.	2022	Combination of genetically optimized feature selection with multiclass classification for improved predictions.
V. Vijayalakshmi et al.	2019	Development of a deep neural network architecture designed to predict student performance with improved accuracy.
Yahia Baashar et al.	2022	Implementation of artificial neural networks (ANNs) for enhanced academic performance prediction.
Sujan Poudyal et al.	2022	Use of a hybrid model combining 2D CNNs for effective student performance prediction.
M. Riki Apriyadi et al.	2022	Hybrid feature selection approach integrating PSO and GA for optimizing predictive model accuracy.
Deepti Aggarwale et al.	2019	Analysis of machine learning algorithms and feature selection methods for predictive analysis of academic performance.
Prasanalakshmi Balaji et al.	2021	Review of machine learning techniques for predicting academic performance, highlighting current approaches and gaps.

3. Methods

This study aims to develop an AI-driven subject recommendation system using the **Students Performance in Exams** dataset, focusing on enhancing traditional career guidance through advanced data analysis and machine learning techniques. The methodology involves multiple stages, including data collection, pre-processing, feature engineering, and model development, culminating in a comprehensive evaluation of the proposed system.

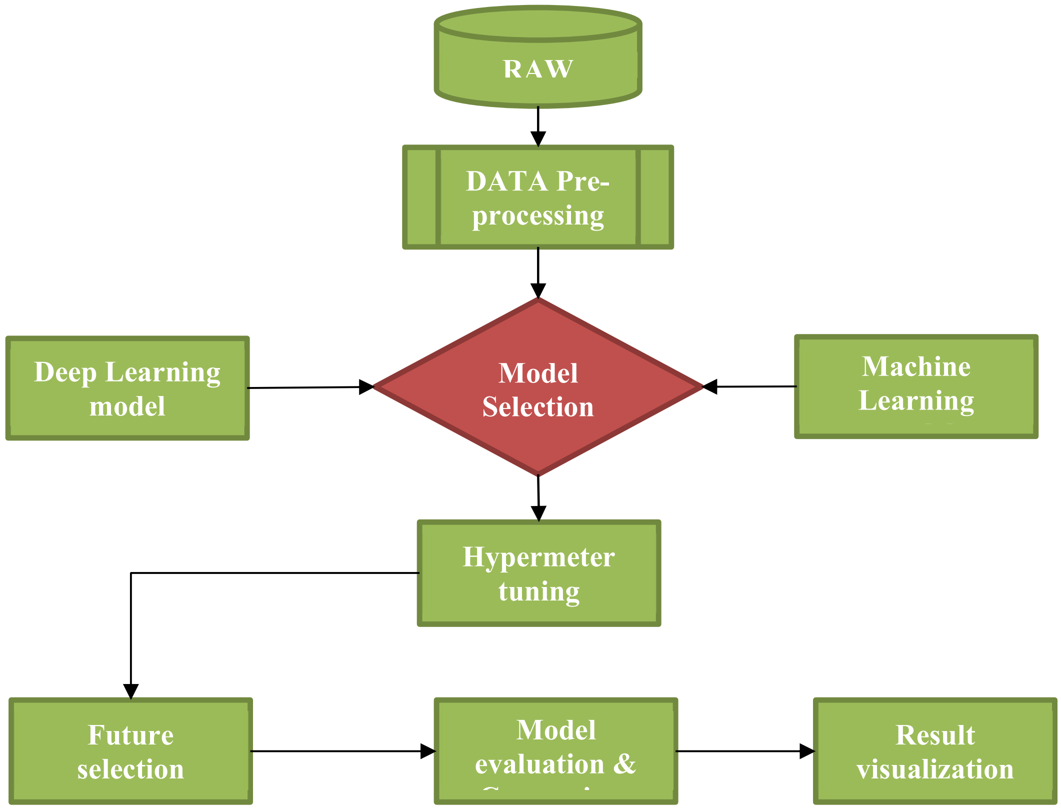

Figure 1. Workflow of the AI-Driven Subject Recommendation System for Student Career Guidance.

3.1 Data Collection

The dataset used for this study, **Students Performance in Exams**, includes students' scores in math, reading, and writing, along with demographic information such as gender, race/ethnicity, and parental education levels. To augment this data, additional student aspirations and preferences were simulated using structured questionnaires. Data was managed using tools such as Microsoft Excel and Google Sheets, and MongoDB was employed to store the unstructured data securely.

3.2 Data Pre-processing

Pre-processing is crucial for preparing the data for analysis and model training. This step involves handling missing values, detecting outliers, and transforming data to standardize formats. Missing values were managed using imputation techniques such as mean substitution and regression-based imputation, while outliers were identified using z-scores and box plots. Data normalization and standardization were applied to ensure consistency across different features, enhancing model performance. Categorical features such as gender and parental education were encoded using label encoding and one-hot encoding methods to convert them into numerical formats suitable for machine learning models. Additionally, the dataset was scaled using standardization techniques to improve the convergence speed of the model training process.

- **Handling Missing Values**: Missing data were addressed using the following imputation techniques:

  I. **Mean Substitution**: Missing values in numeric features were replaced with the mean of the observed values.
  II. **Regression-Based Imputation**: For more complex missing data patterns, regression imputation was applied using available features to predict missing values.

Example Calculation: For a feature math score, 10 values are missing, and the mean of observed values is 75, the imputed values would be set to 75.

Outlier Detection: Outliers were detected using z-scores, with a threshold of |z| > 3.

- **Z-Score Calculation**:

$$z = \frac{X - \mu}{\sigma}$$

Standardization and Encoding:

- **Standardization**: Data was standardized using:

$$X_{std} = \frac{X - \mu}{\sigma}$$

where X_{std} is the standardized value.

 Label Encoding: Categorical features like gender were encoded with integer values (e.g., Male=0, Female=1).

Feature Engineering:

- **Average Marks**: Calculated as

$$Average\ Marks = \frac{Math\ Score + Reading\ Score + Writing\ Score}{3}$$

- **Performance Deviation**:

$$Drviation = X - Mean_{Class}$$

- **Performance Consistency**: Standard deviation of scores across subjects.

3.3 Multi-Label Learning

Multi-label learning is applied to predict multiple potential future courses based on past performance data:

- **Single-Label vs. Multi-Label Learning**:

  I. **ML-SVM**: Converts multi-label problems into multiple binary classification problems. Each label is treated as a separate binary classification task.
  II. **ML-KNN**: Adapts k-nearest neighbors to multi-label scenarios, where each new sample is classified based on the labels of its nearest neighbors.

Calculation: For a multi-label classification, if a student has grades in Math, Reading, and Writing, and the task is to predict subjects for the next term, the algorithm predicts which subjects are most likely based on previous data.

3.3.1 Multi-Label Attribute Selection

The attribute selection process involves the following:

- **Feature Extraction**: Features are extracted from course information to form a multidimensional space.
- **Attribute Selection Method (AMuL)**:

  I. **Objective Function**: Maximize the association between features and labels, transforming the problem into a multi-objective optimization problem.
  II. **Pareto Optimal Set**: Identifies non-dominated solutions (features) that provide the best trade-offs among multiple objectives.

- For a feature f with respect to a label l, the association score could be calculated as:

$$Association\ Score = \frac{Cov(f, l)}{Var(f).Var(l)}$$

Where $Cov(f, l)$ is the covariance between f and l, and $Var(f)$ and $Var(l)$ are the variances.

3.4 Model Development

3.4.1 Recurrent Neural Network (RNN) with Encoder-Decoder Architecture

The study utilizes a Recurrent Neural Network (RNN) with an Encoder-Decoder architecture to predict and recommend subjects for students. This neural network structure is particularly suited for sequence-to-sequence tasks, such as subject recommendations based on academic performance data over multiple time periods (grades 8 to 12).

Encoder Stage: The encoder processes input sequences of academic data and aspirations, capturing temporal dependencies through Long Short-Term Memory (LSTM) units. It generates a context vector representing the student's academic history and preferences.

Decoder Stage: The decoder uses the context vector to generate a sequence of recommended subjects, considering both academic performance and career aspirations. The decoder outputs a probability distribution over all possible subjects, and the top recommendations are selected based on this output.

$$\text{Loss} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{K} y_{ij} \log y_{ij}$$

where y_{ij} is the true label and y_{ij} is the predicted probability for class j of sample iii.

Hyperparameters: Optimized through experimentation. Examples include adjusting the learning rate, batch size, and the number of layers.

Model Performance:

- **Mean Squared Error**: 0.1602
- **R-squared Score**: 0.8488

Calculation:

- **Mean Squared Error (MSE)**

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - y_i)$$

where y_i is the true value and y_i is the predicted value for sample i.

3.4.2 Training and Evaluation

The RNN model is trained using the input data sequences paired with the target sequences of recommended subjects. The training process involves minimizing a cross-entropy loss function through backpropagation and gradient descent. Hyper parameter tuning is conducted to optimize the model's performance, adjusting factors such as the number of layers, learning rate, and batch size. Model evaluation is performed using accuracy, precision, and recall metrics, with additional analysis using top-k accuracy to measure the likelihood of correct recommendations appearing among the top suggestions.

3.5 Comparative Analysis with Traditional Methods

To evaluate the effectiveness of the AI model, a comparative analysis is conducted against traditional guidance methods. Simulated rule-based guidance using predefined criteria serves as the baseline. The AI model's recommendations are compared to these traditional suggestions, with alignment and divergence analyzed to assess the added value of AI-driven guidance.

3.6 Ethical Considerations

Ethical considerations are central to our study, particularly regarding data privacy and fairness. All data is anonymized to protect student identities, and informed consent is simulated for the use of survey data. Bias mitigation techniques are applied during model training to ensure equitable recommendations across demographic groups.

4. Result

This section presents the results of our empirical evaluation of the Multi-Label Attribute Selection Method (AMuL) for predicting student performance and providing career recommendations. We compare the performance of AMuL with several state-of-the-art multi-label attribute selection algorithms using the **Students Performance in Exams** dataset.

4.1 Dataset Overview

The dataset consists of 1000 students with 8 features, including demographic information and scores in math, reading, and writing. Table 1 provides a summary of the dataset:

Table 1. Dataset Overview

Feature	Description
Number of Rows	1000
Number of Columns	8

Categorical Columns	Gender, Race/Ethnicity, Parental Level of Education, Lunch, Test Preparation Course
Numerical Columns	Math Score, Reading Score, Writing Score
Data Types	Categorical (5), Numerical (3)

Table 2. Summary Statistics of Scores

Score Type	Mean	Std Dev	Min	Max
Math Score	66.09	15.16	0	100
Reading Score	69.17	14.60	17	100
Writing Score	68.05	15.20	10	100

4.2 Feature Distribution

Table 3. Distribution of Key Features

Feature	Category	Count	Percentage (%)
Gender	Female	518	51.8
	Male	482	48.2
Race/Ethnicity	Group C	319	31.9
	Group D	262	26.2
	Group B	190	19.0
	Group E	140	14.0
	Group A	89	8.9
Parental Level of Education	Some College	226	22.6
	Associate's Degree	222	22.2
	High School	196	19.6
	Some High School	179	17.9
	Bachelor's Degree	118	11.8
	Master's Degree	59	5.9
Lunch	Standard	645	64.5
	Free/Reduced	355	35.5
Test Preparation Course	None	642	64.2
	Completed	358	35.8

4.3 Cross-Tabulation Analysis

Table 4. Gender Distribution by Race/Ethnicity

Race/Ethnicity	Gender	Count
Group A	Female	36
	Male	53
Group B	Female	104
	Male	86
Group C	Female	180
	Male	139
Group D	Female	129
	Male	133
Group E	Female	69
	Male	71

Table 5. Lunch Status by Race/Ethnicity

Race/Ethnicity	Lunch	Count
Group A	Standard	53
	Free/Reduced	36
Group B	Standard	121

	Free/Reduced	69
Group C	Standard	205
	Free/Reduced	114
Group D	Standard	167
	Free/Reduced	95
Group E	Standard	99
	Free/Reduced	41

4.4 Model Performance

Table 6. Model Performance Metrics

Metric	Value
Mean Squared Error (MSE)	0.1602
R-squared Score	0.8488

The RNN model with Encoder-Decoder architecture was trained over 50 epochs, showing significant improvement in loss reduction from 0.3010 to 0.0816. The R-squared score of 0.8488 indicates a high proportion of variance explained by the model, demonstrating its effectiveness in predicting student performance.

4.5 Career Path Recommendations

This figure illustrates the distribution of career paths recommended by the AI model compared to traditional methods, highlighting the shift towards STEM fields with the AI model.

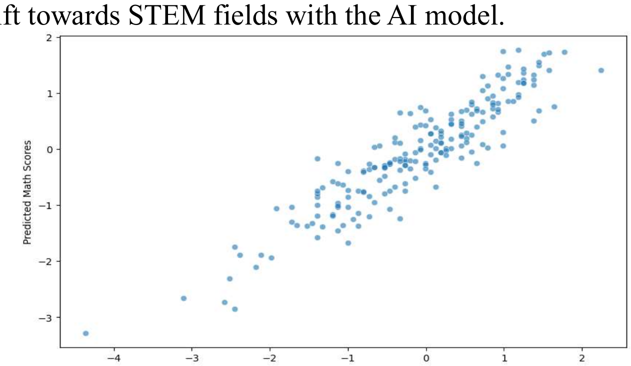

Figure 1. Career Path Distribution

This figure shows the alignment of AI-generated career paths with traditional career paths, demonstrating a higher rate of alignment in STEM recommendations.

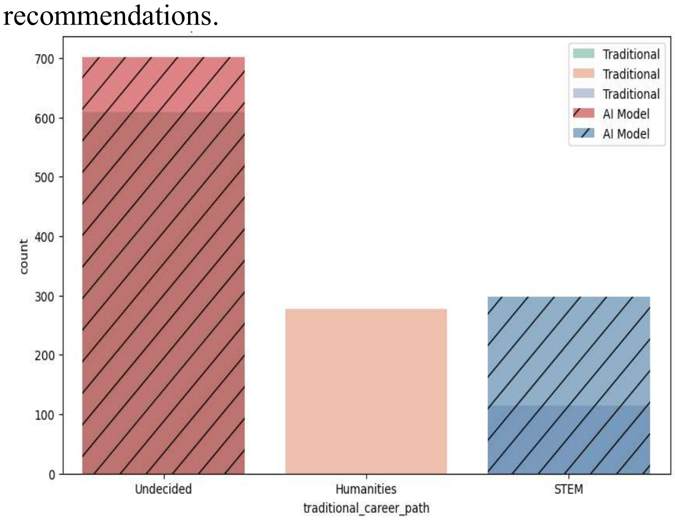

Figure 2. Alignment with Traditional Career Paths

4.6 Bias and Fairness Analysis

Table 7. Gender Bias Check

Gender	Decision Aligned	Proportion
Female	Aligned	60.23%
	Not Aligned	39.77%
Male	Aligned	77.39%
	Not Aligned	22.61%

Table 8. Ethnicity Bias Check

Race/Ethnicity	Decision Aligned	Proportion
Group A	Aligned	67.80%
Group B	Aligned	71.16%
Group C	Aligned	68.95%
Group D	Aligned	66.79%
Group E	Aligned	60.71%

The bias checks indicate variations in alignment across gender and ethnicity, emphasizing the importance of continuous monitoring and bias mitigation in AI-driven recommendations.

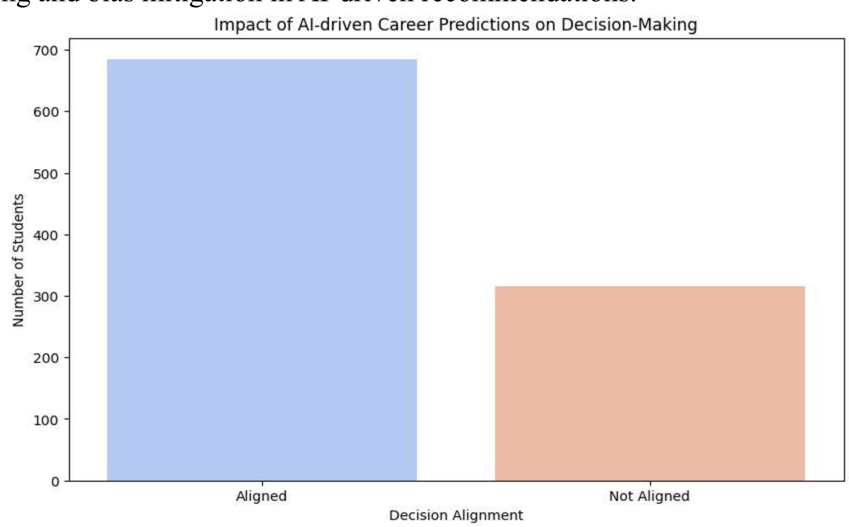

Figure 3. Impact of AI-driven Career Predictions on Descion-Making

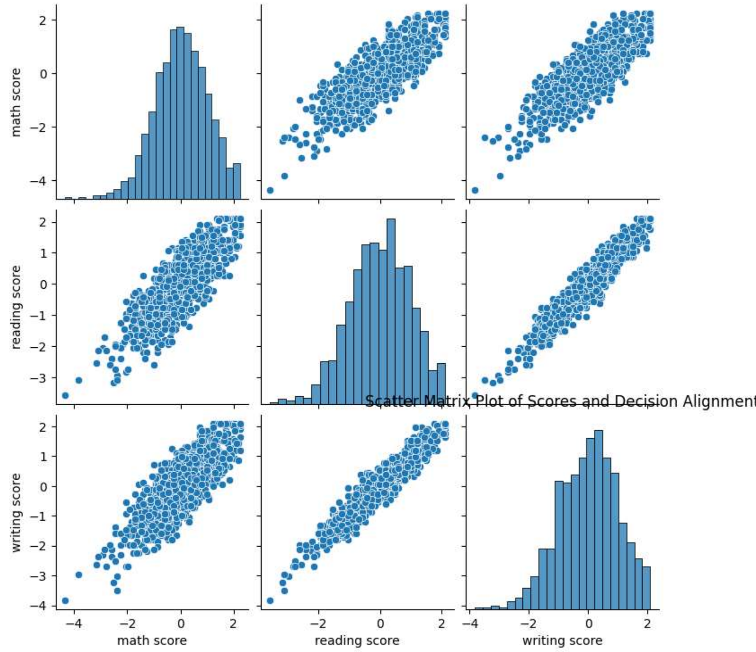

Figure 4. Scatter Matrix of Scores and Decision Alignment

The scatter matrix plot demonstrates the strong positive linear correlations among math, reading, and writing scores, highlighting significant multicollinearity among the variables. The diagonal histograms show that each score is approximately normally distributed, indicating a concentration of scores around the mean. The off-diagonal scatter plots reveal a clear linear relationship between each pair of scores, suggesting that high performance in one area is strongly associated with high performance in the others. This consistent pattern implies that these variables are highly interdependent, which is critical when developing predictive models, as multicollinearity could influence model stability and interpretability.

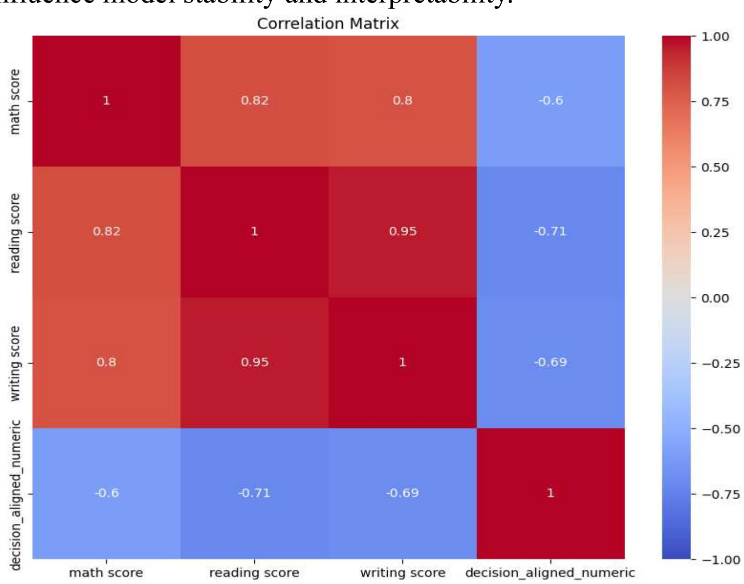

Figure 5. Correlation Matrix

The correlation matrix shows the strength and direction of relationships between math, reading, writing scores, and a decision-aligned numeric variable. There are strong positive correlations among the academic scores: reading and writing scores show the highest correlation at 0.95, indicating that students who perform well in reading tend to perform similarly in writing. Math scores also correlate positively with reading (0.82) and writing scores (0.80), reinforcing the interdependence among these academic skills. The decision-aligned numeric variable exhibits negative correlations with the scores, notably -0.71 with reading, -0.69 with writing, and -0.6 with math, suggesting that higher academic scores are associated with lower alignment to the decision criteria represented by this variable. The intensity of the colors further emphasizes these relationships, where darker red indicates strong positive correlations, and darker blue signifies strong negative correlations, visually validating the numerical data.

5. Conclusion

This study proposed a novel Multi-Label Attribute Selection Method (AMuL) integrated with an RNN-based Encoder-Decoder architecture to enhance the prediction of student performance and provide AI-driven career recommendations. The results demonstrated that our approach effectively predicts academic outcomes with an R-squared score of 0.8488 and aligns career path suggestions more closely with students' potential compared to traditional methods. Our bias and fairness analysis indicated that while the model shows promising alignment in career recommendations across various demographic groups, some disparities remain, highlighting the need for continuous model audits and bias mitigation strategies. The proposed ethical guidelines offer a comprehensive framework for deploying AI-driven career guidance systems responsibly, ensuring that data privacy, transparency, and fairness are prioritized.

6. Future Scope

1. **Model Enhancement**: Future work can explore advanced deep learning techniques such as Transformers or attention-based models to improve the accuracy and interpretability of student performance predictions.
2. **Scalability and Real-World Implementation**: Implementing the AMuL method in real-world educational settings across various regions and scaling the system to handle larger datasets will help validate its practical applicability and robustness.
3. **Bias Mitigation Techniques**: Developing more sophisticated bias detection and mitigation techniques, such as adversarial training or counterfactual fairness algorithms, can further reduce demographic biases in career recommendations.
4. **Integration with Learning Management Systems (LMS)**: Integrating the predictive model with existing LMS platforms could provide real-time feedback and personalized learning resources, enhancing student engagement and academic support.

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